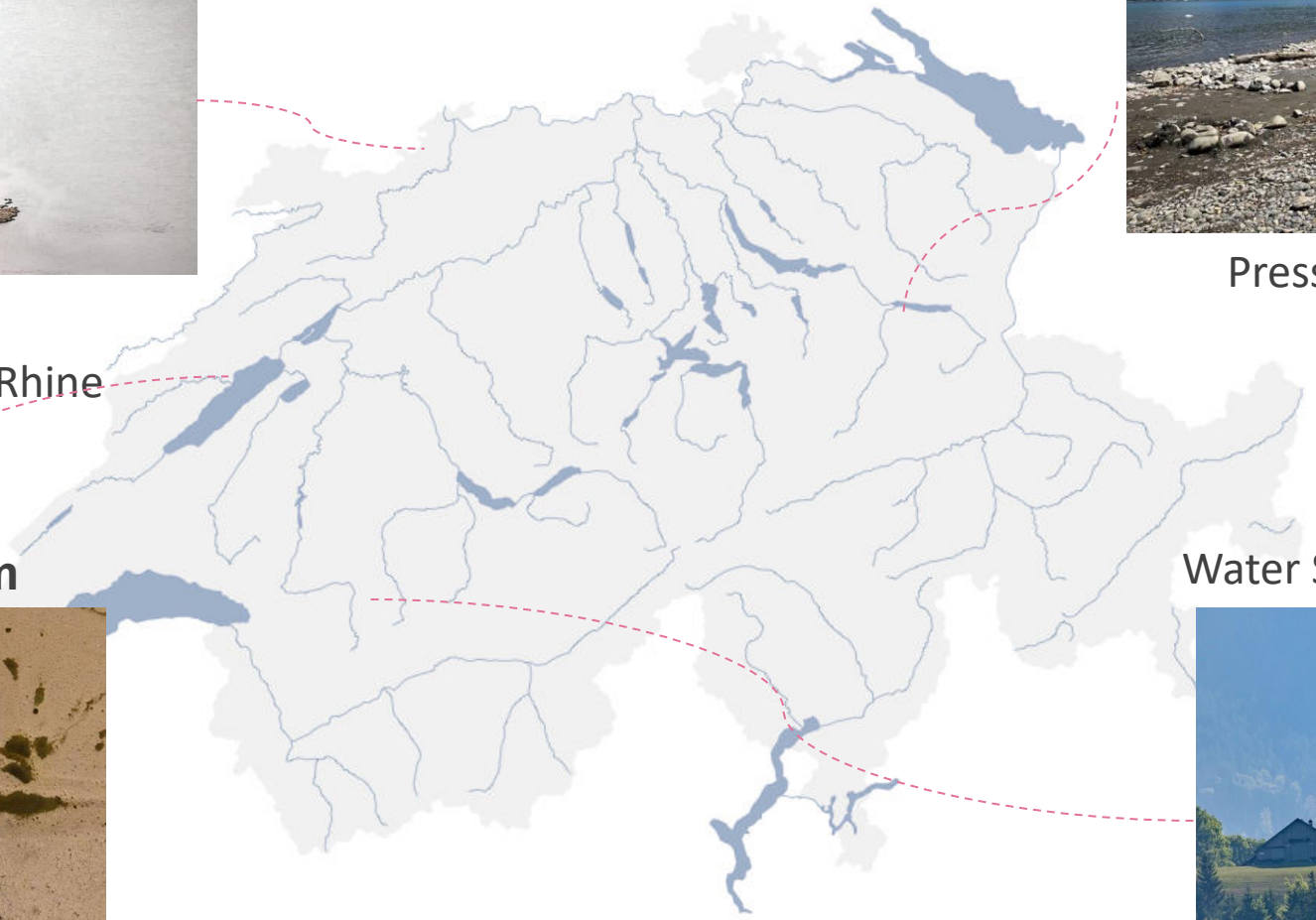
Sub-seasonal drought forecasting in the European Alps with EFAS data in a machine-learning-aided hybrid approach

Annie Y.-Y. Chang, Konrad Bogner, Maria-Helena Ramos, Shaun Harrigan, Ryan Padrón, Christian M. Grams, Daniela I.V. Domeisen, Massimiliano Zappa

Droughts in Switzerland

Disruption of Goods
Transportation in River Rhine
Source: SRF

Pressure on **Ecosystem**
Source: Watson



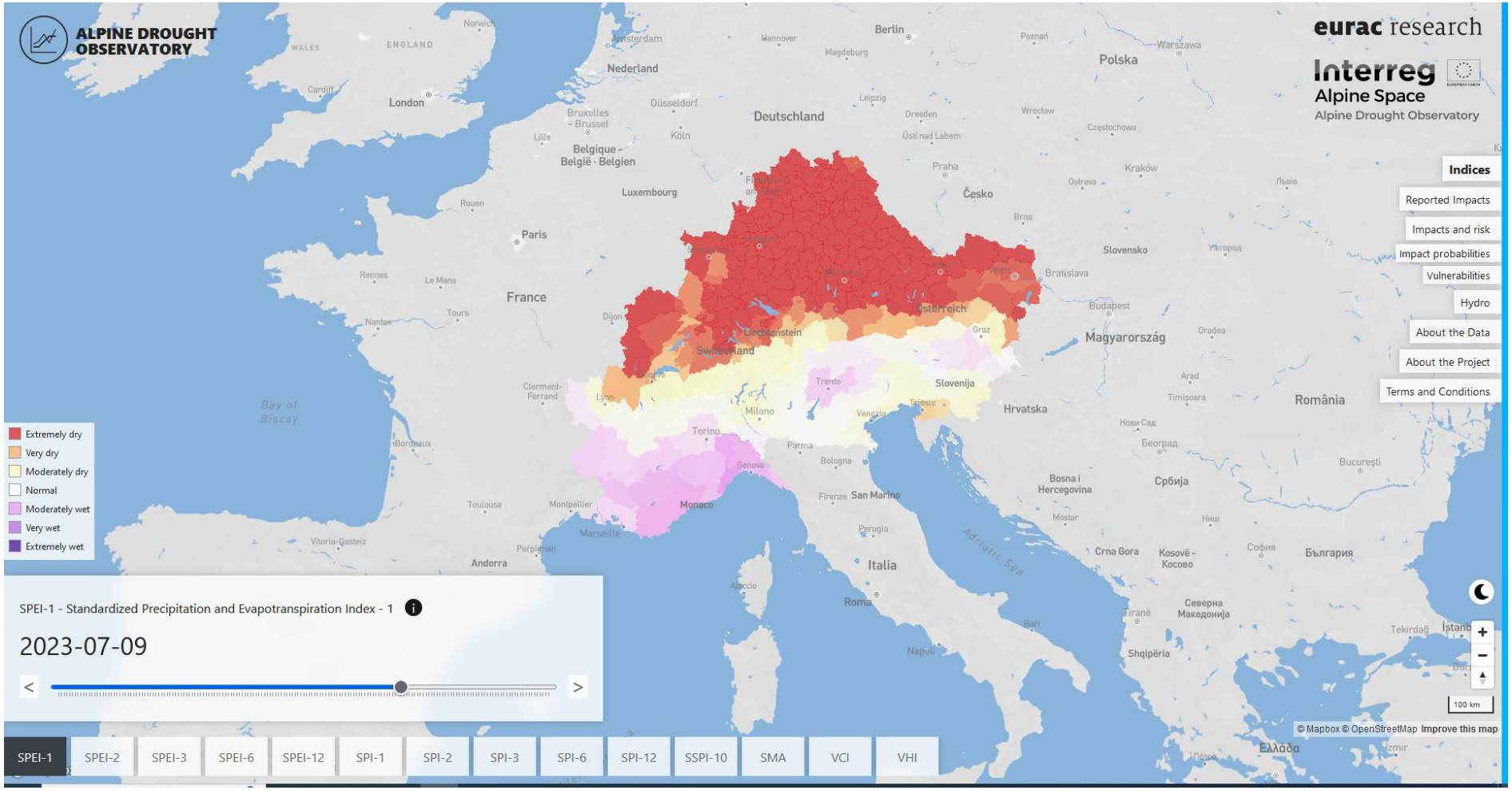
Source: NZZ
Low Lake Level for **Tourism**

Source: The Atlantic
Water Shortage for **Cattle** in Alps

Hydrological Drought in the European Alps

IT Italy
FR France
CH Switzerland
DE Germany
AT Austria
SI Slovenia

Interreg Alpine Space
Alpine Drought Observatory
European Regional Development Fund



European Alpine Space

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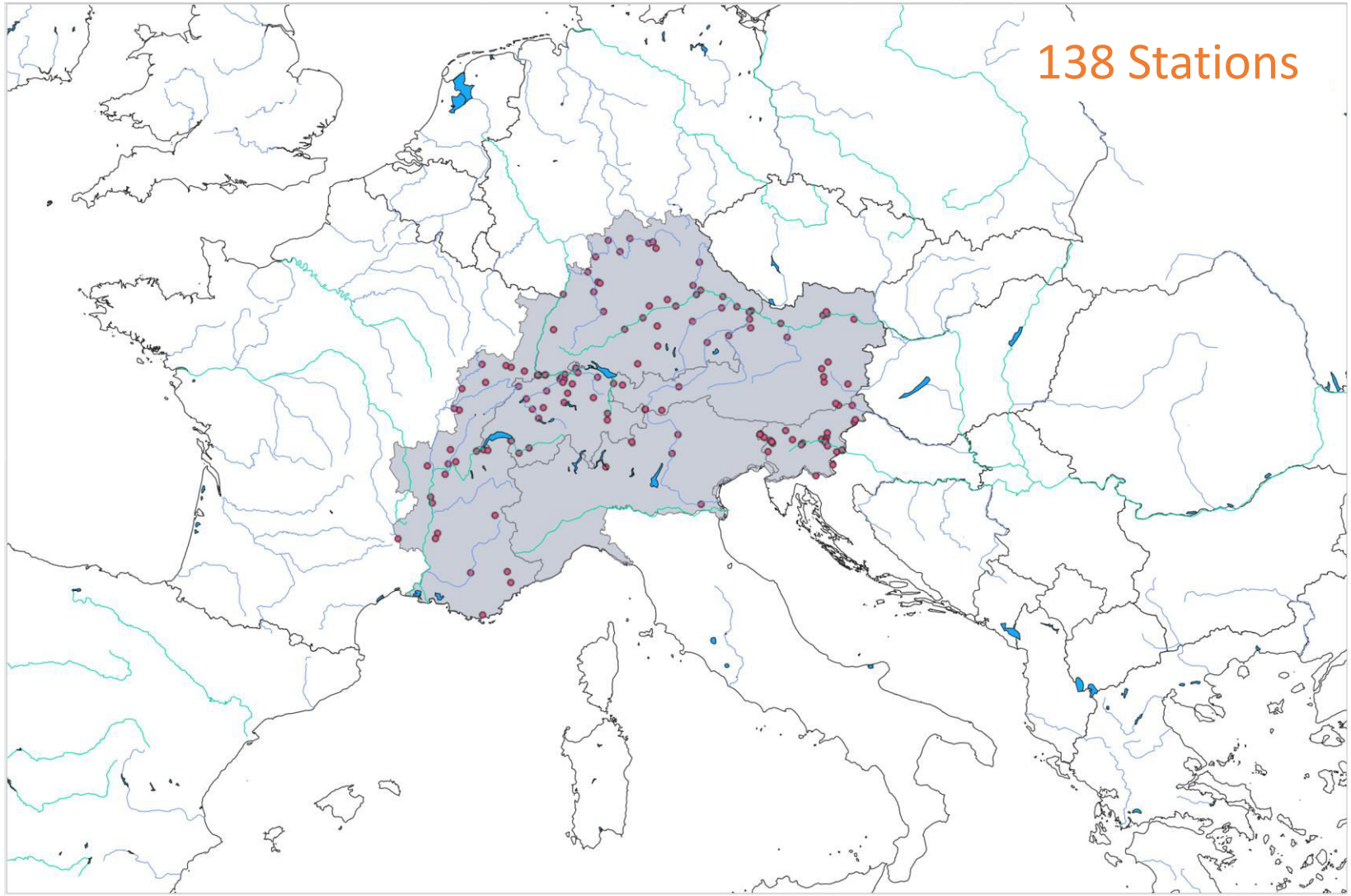


EFAS - The European Flood Awareness Systems

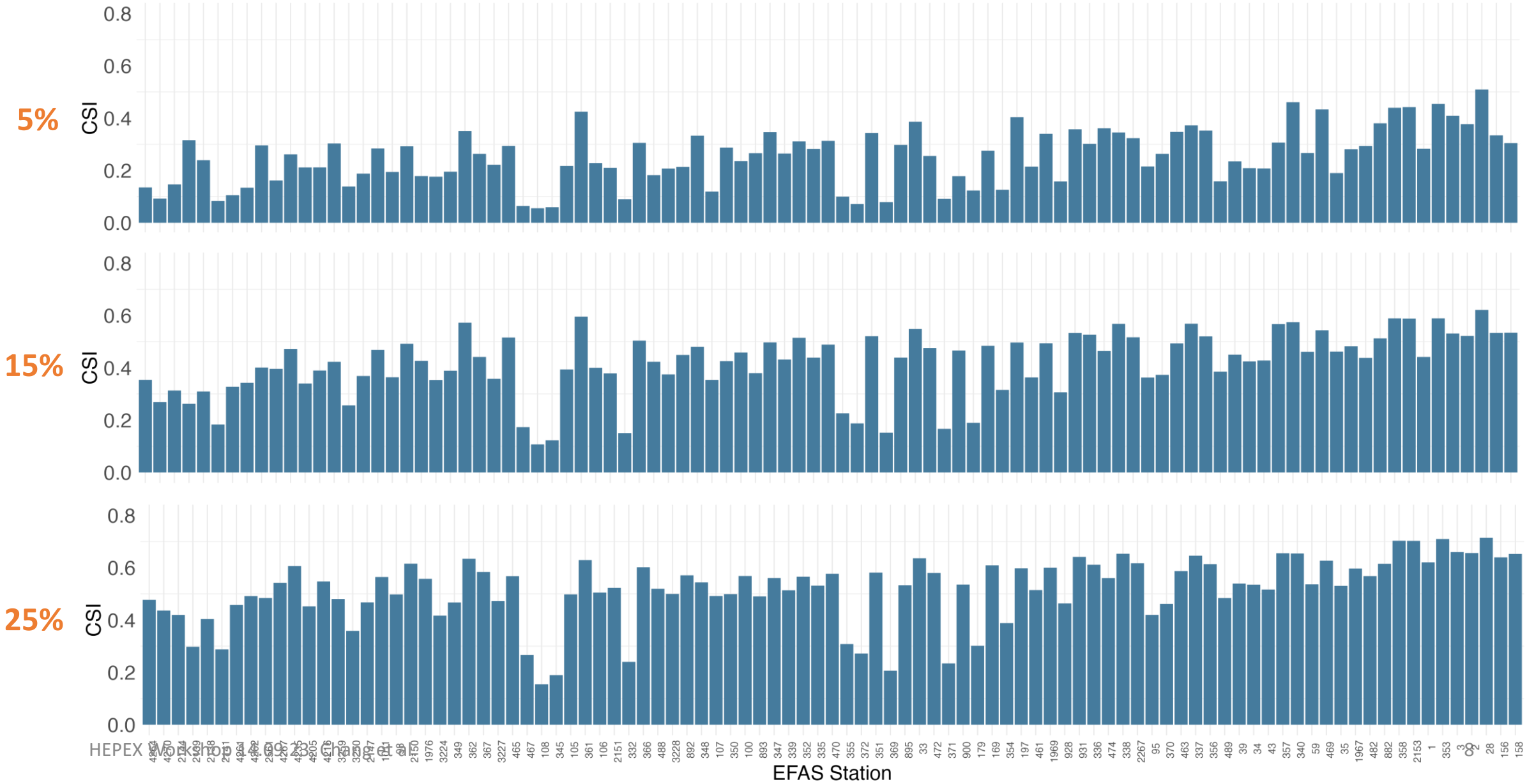
- Continental model in operation since 2012 by ECMWF
- Pan-European products:
  - overview maps of flood probabilities up to 15 days in advance
  - seasonal streamflow outlooks
  - flood impact assessment
  - flash-flood risk
- V4.0: ~5km
- Data:
  - Reanalysis 1990 – 2019
  - Reforecast 1999 - 2018

KGE (-∞ to 1)

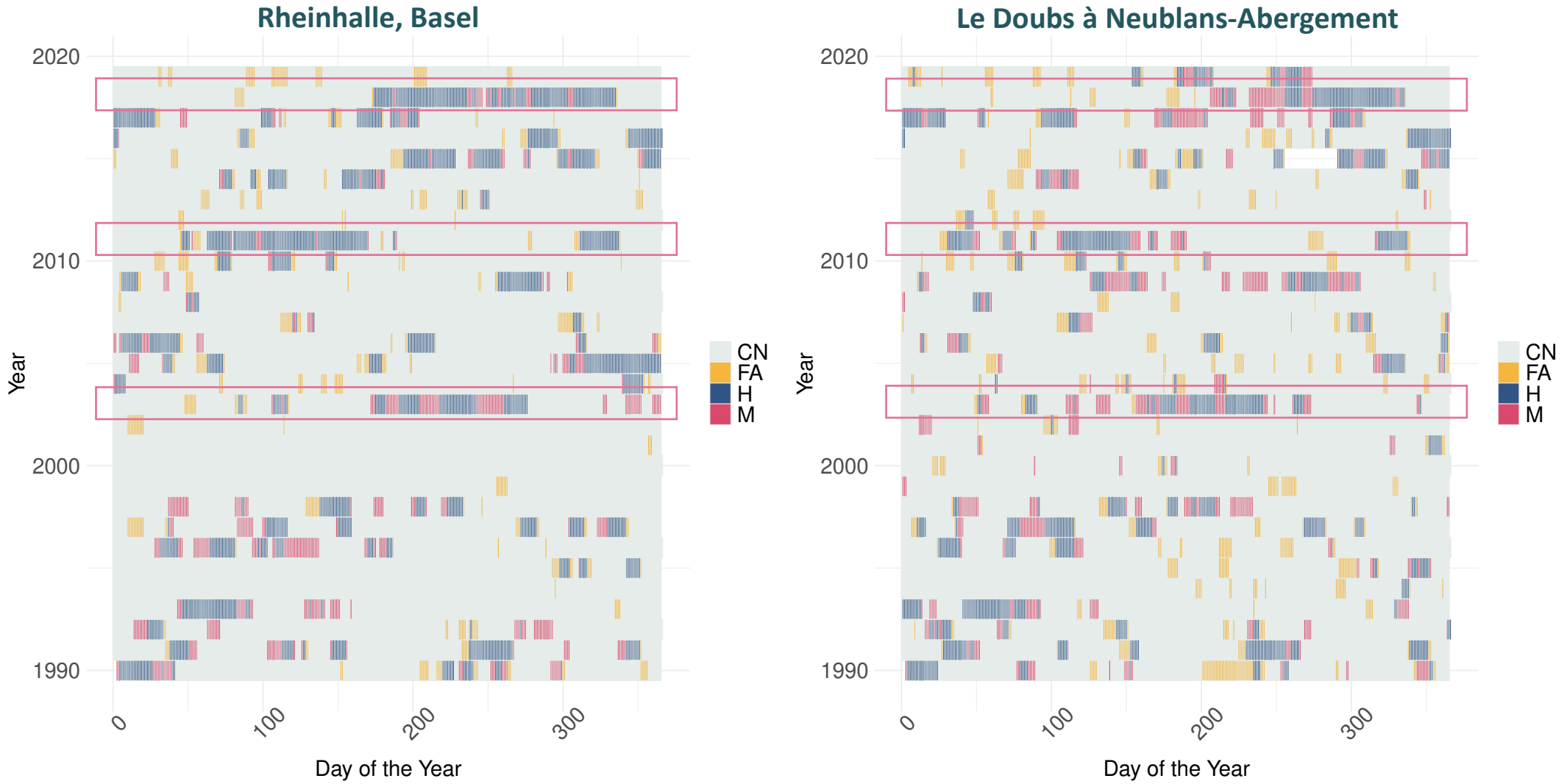
- EFAS reanalysis streamflow data 1990-2019
- 7-day moving window
- 95 stations
- 50 – 95970 km^2

Critical Success Index (CSI 0 - 1)

$$CSI = \frac{hits}{hits + misses + false\ alarms}$$



15% low-flow threshold : Hits (H), Misses (M), False Alarms (FA), and Correct Negatives (CN)



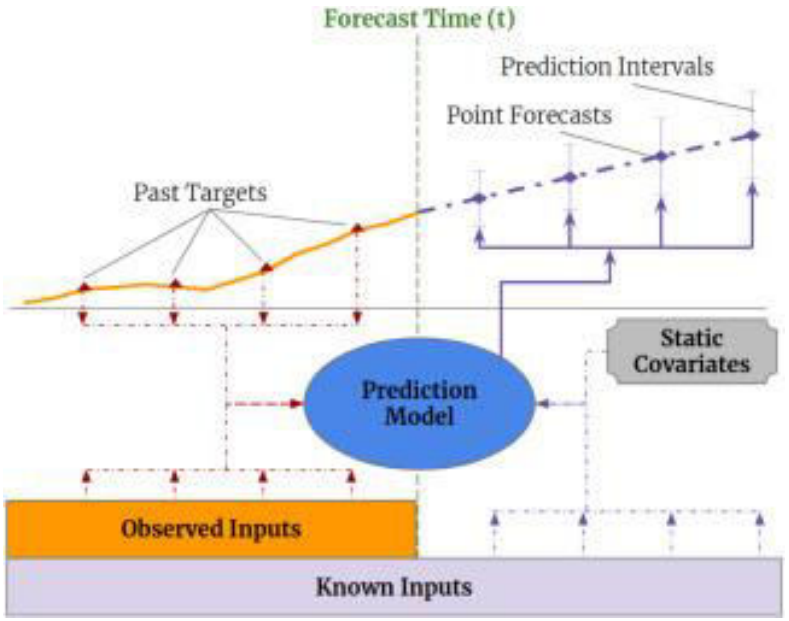
Key Findings:

- Model performance deteriorates for the more extreme drought events
- Catchment size and location have no clear correlation with model performance
- EFAS tends to simulate shorter events
- EFAS tends to simulate more water in summer

How can we improve this?

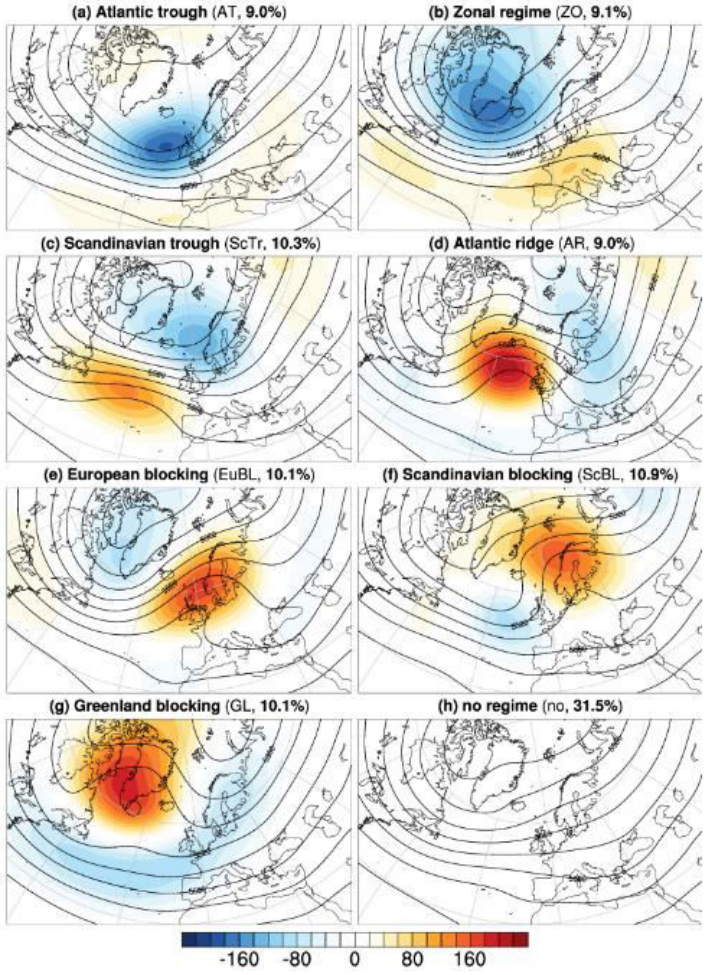
Deep Learning: Temporal Fusion Transformer (TFT)

- What?
  - Combines LSTM and Transformer models
  - Uses LSTM layers to encode local temporal patterns and a transformer layer to capture global dependencies.
- Why?
  - Exploratory
  - Attention weight for feature importance - more interpretable than LSTM



(Lim et al., 2021)

European Weather Regimes



Source: C. M. Grams (2019)

*"Weather regimes are **quasi-stationary, recurrent, and persistent states** of the large-scale extratropical circulation that describe most of the multi-day variability in the Atlantic-European region."*

- Christian Grams at KIT

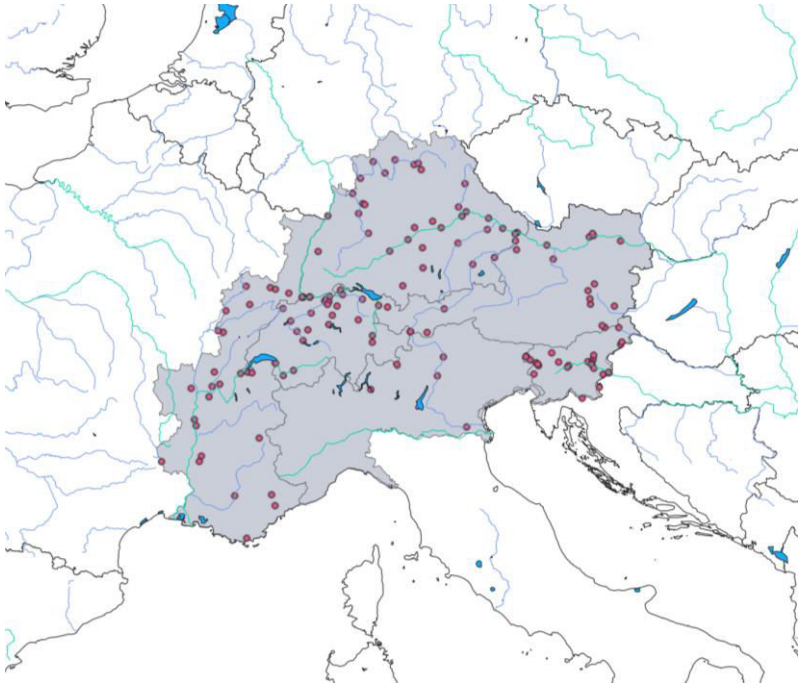
Exploring the Use of European Weather Regimes for Improving User-Relevant Hydrological Forecasts at the Subseasonal Scale in Switzerland

ANNIE Y.-Y. CHANG,[a,b] KONRAD BOGNER,[a] CHRISTIAN M. GRAMS,[c] SAMUEL MONHART,[d] DANIELA I. V. DOMEISEN,[b,e] AND MASSIMILIANO ZAPPA[a]

Local Hydrological Events

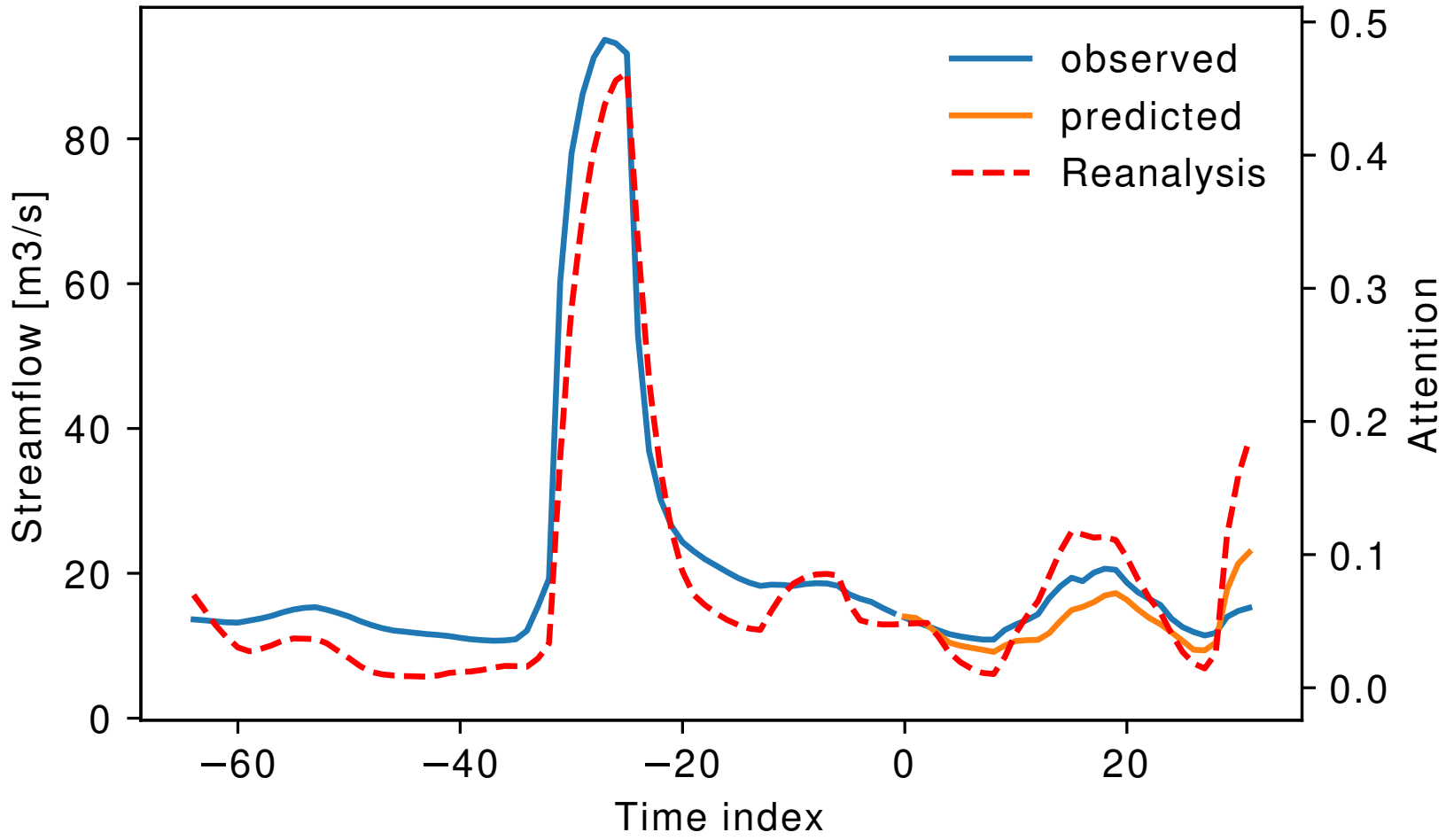
Post-processing EFAS

- Multiple time series: **One model** for all stations
- Multi-horizon forecasting: Daily quantile predictions from 1 to **32 days** lead time
- Target: **Q_obs**
- Heterogeneous features: **EFAS discharge, Weather Regime indices (7), date, catchment area, elevation**
- Training + Validation: continuous time series of **observed/ reanalysis** data (June 1999 – May 2009)
- Testing: **reforecast** data (June 2009 to Dec. 2012)
- Interpretable predictions: Information on **variable importance**

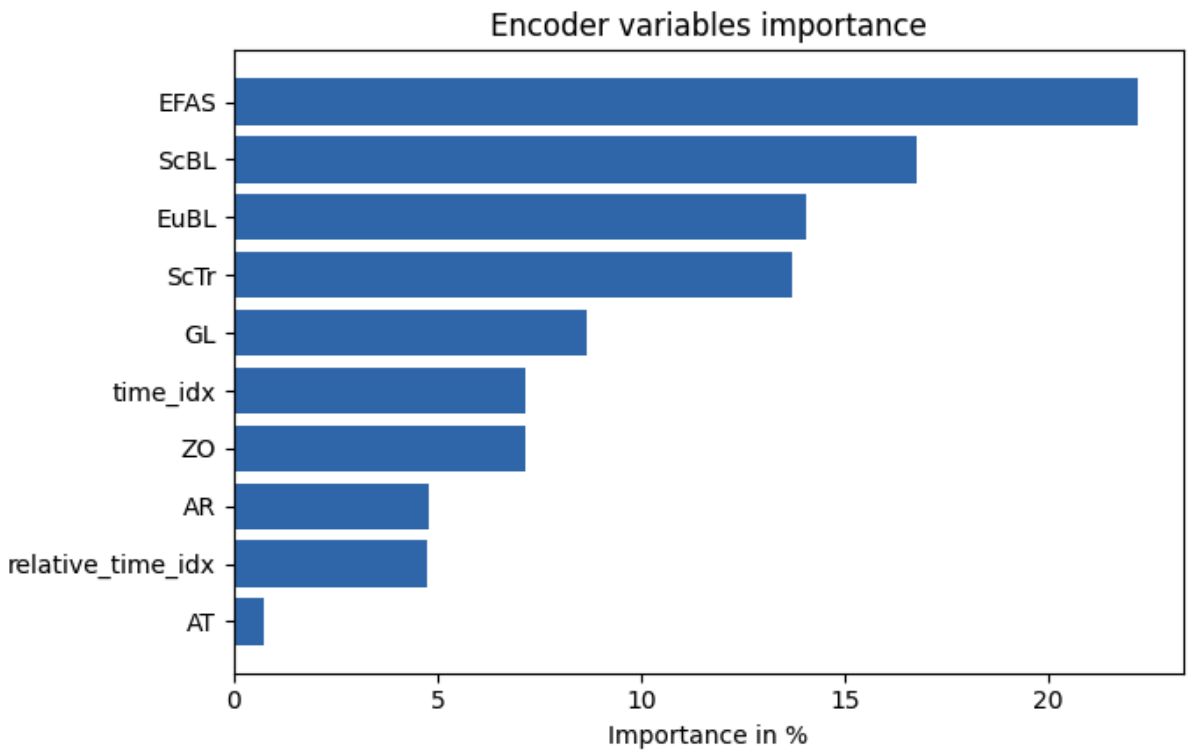


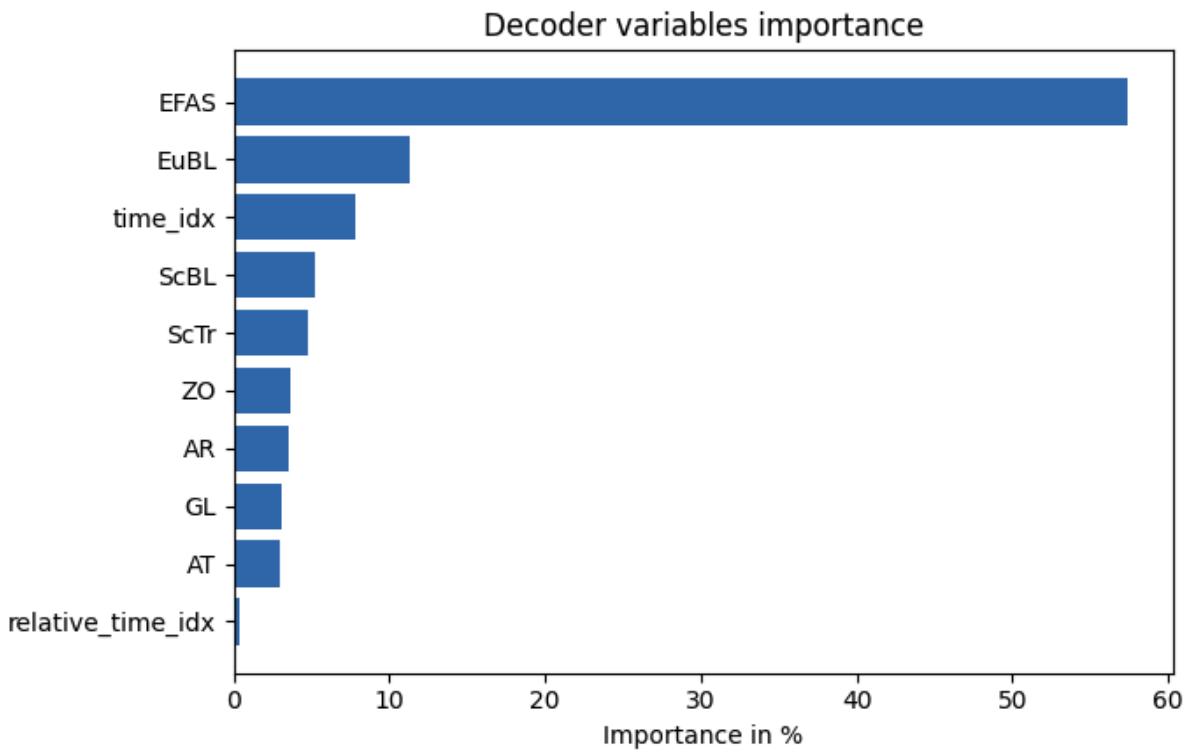
64 day encoder period	32 day decoder period

Preliminary Results – 2011-05-15 Laško (SI)



Feature Importance





We want to understand…

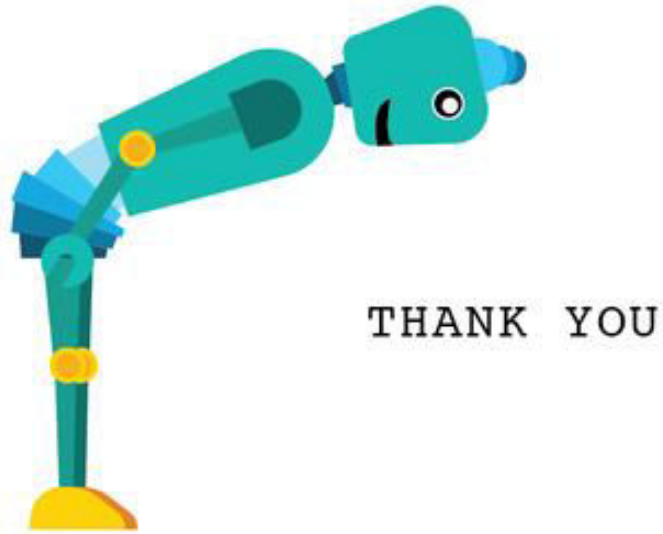
How much skill improvement can we achieve with the hybrid set up for monthly drought prediction using EFAS data?

- Any spatial pattern in the Alpine region?
- What are the main features driving the improvements and why?

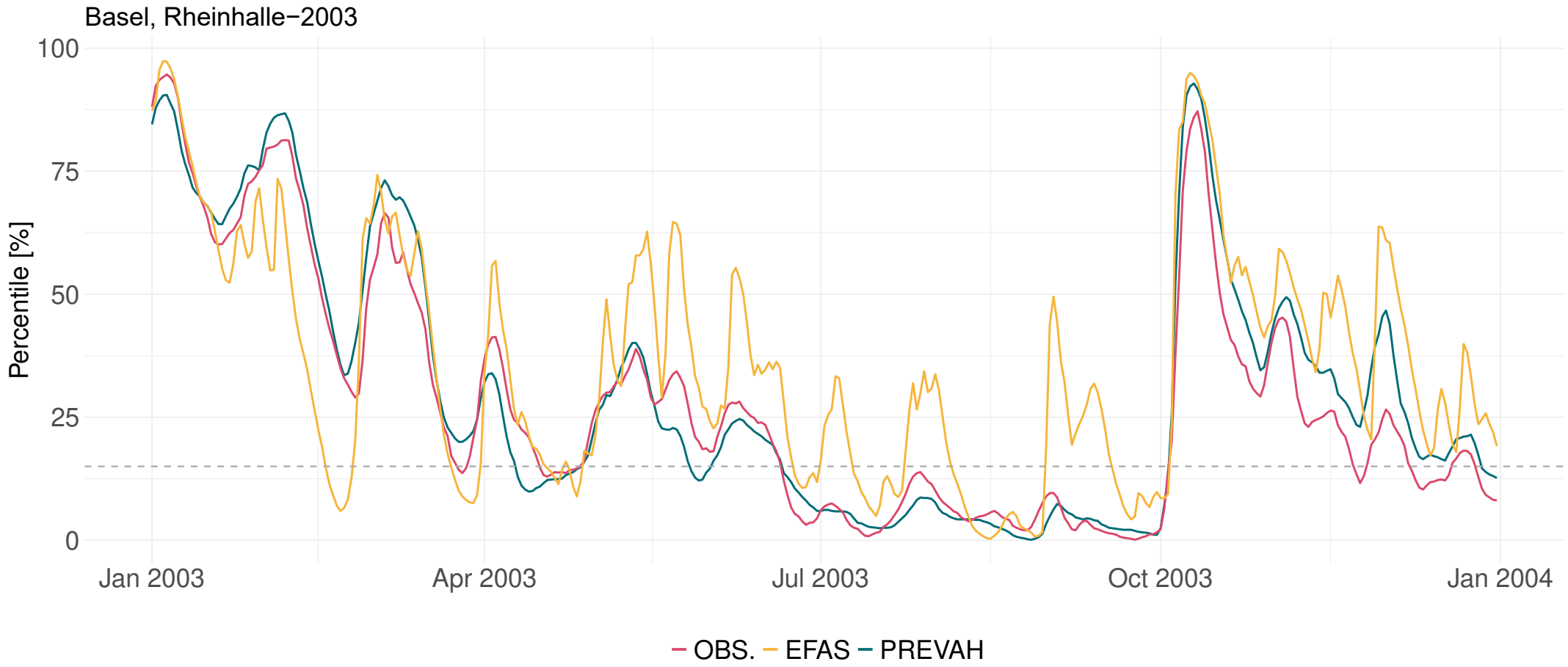
Next Steps & Challenges

- Hyper parameter tuning
- Additional static feature:
  - Lake damping factor
  - Glacier coverage
  - Drought index
  - …
- How to train the model for low flow?

SCAN ME!

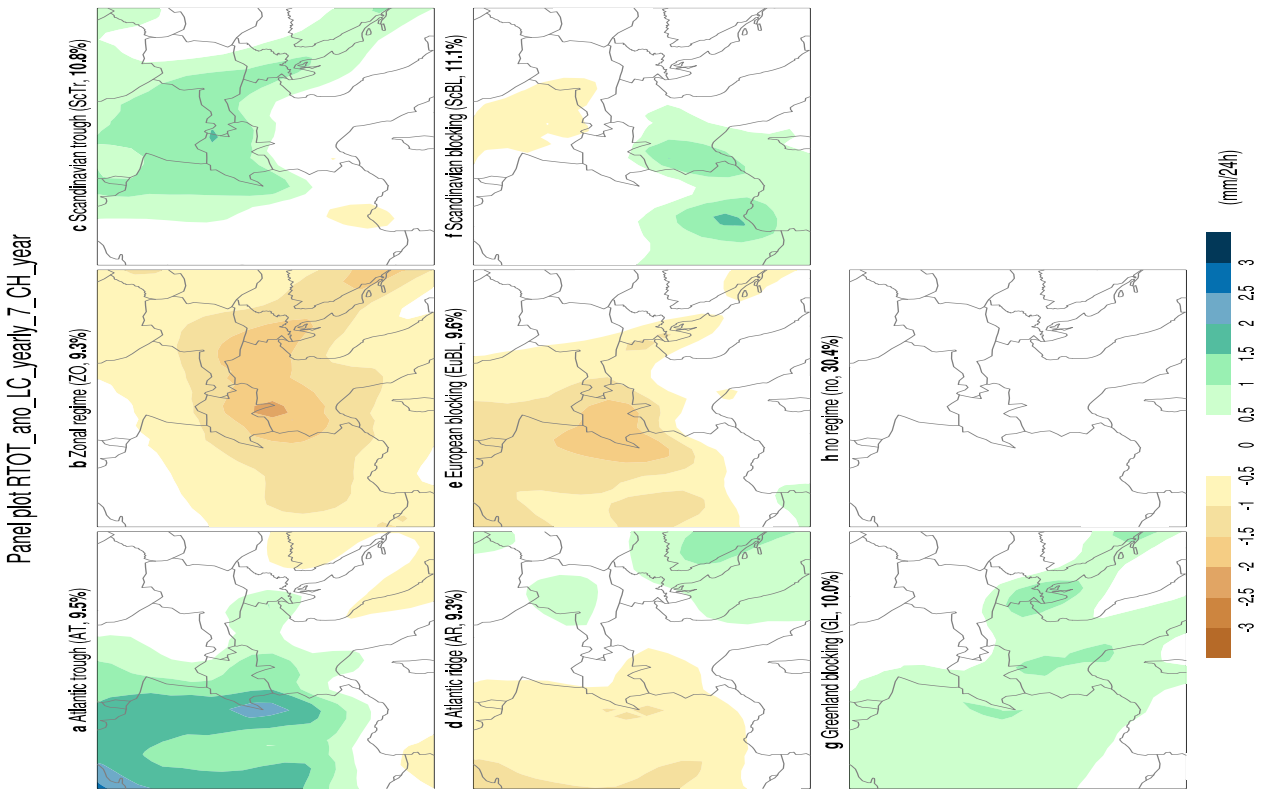


Bakcup - Case Studies: Rheinhalle, Basel 2003



Backup - European Weather Regimes

Precipitation Anomaly



Temperature Anomaly